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Discrimination power control for adaptive target tracking applications

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Abstract

This report addresses the problem of discrimination power in target tracking applications. More specifically, a closed-loop approach to adapt the sensing and tracking operations is proposed and compared to the conventional open-loop and static approach. The objective is to control and maintain, over a certain volume of interest and by way of clustering and scheduling strategies, the level of discrimination power required by the mission objectives. The control strategy is based on two cascade loops. The outer loop uses clustering techniques to characterize the volume of interest in terms of discrimination power. This high level information is exploited by the inner loop to compute optimal track update and sensor scheduling strategy. The presented results show that the discrimination power can be improved by adapting the target tracking operations. This improvement could benefit tactical military surveillance operations such as contact/track correlation, target engagement, target identification and classification.

Résumé

Le travail présenté dans ce rapport porte sur le problème de la capacité discriminatoire dans des applications de pistage de cibles. Plus précisément, une approche en boucle fermée, qui permet d'adapter les opérations de détection et de pistage, est proposée et comparée à une méthode conventionnelle statique en boucle ouverte. L'objectif poursuivi est de contrôler et de maintenir, pour un certain espace d'intérêt et à l'aide de techniques de regroupement de données et de gestion de tâches, le niveau de capacité discriminatoire requis pour répondre aux objectifs d'une mission. La stratégie de contrôle est basée sur deux boucles imbriquées. La boucle externe utilise des techniques de regroupement de données pour caractériser l'espace d'intérêt sur la base de la capacité discriminatoire. Cette information de haut niveau est alors exploitée dans une boucle interne qui détermine une stratégie optimale de gestion de la mise à jour des pistes. Les résultats obtenus montrent que la capacité discriminatoire peut être améliorée en adaptant le pistage de cibles. L'amélioration ainsi apportée pourrait profite r aux opérations militaires de surveillance telles que la corrélation mesures/pistes, l'identification, la classification et l'engagement de cibles.

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Executive summary

Discrimination power control for adaptive target tracking applications

A. Benaskeur, F. Rhéaume; DRDC Valcartier TR 2008-016; Defence R&D Canada – Valcartier; July 2008.

In military Command and Control applications, surveillance and target tracking aim at providing accurate and timely identification, classification, and kinematics information about the entities within the volume of interest. Modern surveillance and tracking systems have been making increasing use of data fusion technology and tools to achieve their mission's goals and objectives. This work addresses the problem of discrimination power within the framework of adaptive data fusion.

In this work discrimination power is defined as the capability to distinguish objects based on their track information. Two different levels of discrimination power are defined, the signal and the statistical level. The presented target tracking problem concentrates on the statistical level. According to that, different discrimination power measures are suggested: coverage intervals, Mahalanobis distance and chi-squared testing. Because the discrimination power is understood as a critical factor for operations such as contact/track correlation, target identification and classification, we propose a method that adaptively controls it within the tracking system. This discrimination power control should also benefit to target engagement operations, which require a high discrimination power in order to maximize the chance of threat neutralization and minimize the risk of collateral damages.

The suggested discrimination power control method rely on concepts of adaptive data fusion. The adaptation uses a two-level cascade loop, the objective of which is controlling discrimination power over a certain volume of interest. The outer-loop characterizes the whole volume of interest based on the concept of discrimination power. Using clustering and classification techniques, distinct regions are created and managed dynamically based on the targets' spatial distribution. The inner-loop controls discrimination power over the volume of interest by an appropriate selection of the track update frequency and sensor scheduling within each distinct region. Three different scheduling methods are proposed: time-slice, minimum intra-cluster discrimination power and round-robin. All the methods rely on clusters of tracks, but only time-slice and minimum intra-cluster discrimination power adaptively control the track update periods. Round-robin uses a classical open-loop strategy.

A set of scenarios, with varying target densities, was simulated to test different discrimination power control strategies. The scenarios consider a single sensor that can switch the

direction of its beam instantly. The presented results have shown that the discrimination power can be improved by adapting the target tracking operations. The time-slice scheduling algorithm proved to be better than minimum intra-cluster discrimination power and than the open-loop round-robin strategy. The time-slice approach was able to maintain a higher discrimination power in regions with high target densities.

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Discrimination power control for adaptive target tracking applications

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Dans les applications militaires de commandement et contrôle, les opérations de surveillance et de pistage de cibles visent à fournir de manière précise et rapide de l'information sur l'identification, la classification ainsi que sur la cinématique des cibles présentes dans un espace d'intérêt. Les systèmes de surveillance modernes font de plus en plus appel aux technologies et aux outils de fusion de données pour réaliser les objectifs propres à leur mission. Ce travail porte sur le problème de la capacité de discernement, présenté dans le cadre de la fusion adaptative de données.

La capacité de discernement est définie, dans ce travail, comme la capacité de distinguer des objets entre eux, sur la base de l'informaiton contenue dans les pistes. La capacité de discernement se divise en deux niveaux, le niveau du signal et le niveau statistique. Ce dernier sera étudié dans ce travail. À ce propos, différentes mesures de la capacité de discernement sont suggérées : intervalles de couverture, distance de Mahalanobis et test du chi-carré. La capacité de discernement étant considérée comme un facteur critique pour les opérations telles que la corrélation mesure/piste, l'identification et la classification, une méthode pour contrôler adaptativement la capacité de discernement, dans un système de pistage, est proposée. Le contrôle adaptatif de la capacité de discernement pourrait également profiter aux opérations d'engagement de cibles. Ces dernières requièrent un grande capacité de discernement afin de maximiser la probabilité de neutralisation de la menace et de minimiser le risque de dommages collatéraux.

La méthode de contrôle de la capacité de discernement proposée se base sur des concepts de fusion adaptative de données. L'adaptation est réalisée grâce à deux boucles en cascade. L'objectif poursuivi est de contrôler la capacité de discernement pour un certain volume d'intérêt. La boucle externe définit le volume d'intérêt sur la base de la capacité discriminatoire. À l'aide de techniques de regroupement, différentes régions de l'espace sont créées et gérées dynamiquement selon la distribution spatiale des cibles observées. La boucle interne contrôle la capacité discriminatoire par la détermination des stratégies de mise à jour des pistes pour chaque région identifiées du volume d'intérêt. Trois différentes stratégies de mise à jour sont proposées : "tranche de temps", "capacité de discernement minimale intra-groupe" et "à tour de rôle". Toutes ces méthodes se basent sur le regroupement de cibles mais seulement "tranche de temps" et "capacité de discernement minimale intra-groupe" sont adaptatives. La méthode "à tour de rôle" utilise la stratégie classique en boucle ouverte.

Des scénarios avec différentes densités de cibles ont été simulés afin de tester les stratégies développées sur le contrôle de la capacité discriminatoire. Un capteur unique, capable de diriger son faisceau de manière instantanée, est utilisé. Les résultats obtenus montrent qu'il est possible d'améliorer la capacité discriminatoire en adaptant les opérations de pistage. L'algorithme "tranche de temps" s'est révélé meilleur que celui basé la "capacité de discernement minimale intra-groupe" et que l'algorithme "à tour de rôle". L'algorithme "tranche de temps" a été en mesure de maintenir une capacité de discernement plus élevée dans les régions à haute densité de cibles.

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1 Introduction

In military Command and Control (C^2) applications, surveillance and target tracking [1, 2, 3, 4] aim at providing accurate and timely detection, identification, classification, and kinematics information about the entities within the Volume Of Interest (VOI). Modern surveillance and tracking systems have been making increasing use of data fusion technology and tools [5, 6, 7] to achieve their mission's goals and objectives. To gain higher performance, a modern data fusion system needs an active feedback or adaptation. The adaptation may concern the data fusion process itself or the related sensor management problem. This corresponds to Level 4 of the JDL model proposed by the US DoD Joint Directors of Laboratories sub-panel [8]. Level 4 has been removed from the latest version [9] of the JDL model, since it is viewed as a resource management problem.

This work addresses the problem of discrimination power characterization and control within the broader paradigm of adaptive data fusion [10, 11]. More specifically, the report presents the problem of adapting the target tracking operations and attempts to demonstrate the benefits of such adaptation compared to the classical open-loop operation mode. Note that our definition of adaptive data fusion corresponds of the definition of Level 4 in the two previous versions of the JDL [8, 12] and to the concept of levels' refinement in the current version [9].

Target tracking provides estimations of the targets' states represented by probability distributions of the states, which reveal the uncertainty about the state values. In situations involving multiple targets, the latter may come too close to be clearly distinguishable from each other by the tracking system. Targets are said to be distinguishable when the overlap between their spatial probability distributions is below a specific level. The non-overlapping portion of the spatial probability distributions expresses a dissimilarity relation measured in terms of the distance between the spatial probability distributions [13]. This dissimilarity relation among tracks is referred to, in this report, as discrimination power. The latter is understood as a critical factor for operations such as contact/track correlation, target identification and classification. Its impact may even be more critical for target engagement operations. Given this criticality, a high discrimination power is often required to maximize the chance of threat neutralization and minimize the risk of collateral damages.

The above mentioned discrimination power notion is used as an adaptation enabler for target tracking operations. This adaptation is achieved thanks to a two-level cascade loop, the objective of which is controlling discrimination power over a certain volume of interest. The outer-loop characterizes the whole volume of interest based on the concept of discrimination power. Using clustering and classification techniques, distinct regions are created and managed dynamically based on the targets' spatial distribution. The inner-loop controls discrimination power over the volume of interest by an appropriate selection of the track update frequency and sensor scheduling within each distinct region.

The remaining part of the report is organized as follows. First, Chapter 2 introduces data fusion in military operations. Chapter 3 presents and defines the discrimination power problem. Thereafter, Chapter 4 discusses the control of discrimination power in target tracking as a special application of the adaptive data fusion paradigm. Finally, target tracking scenarios are presented in Chapter 5, along with the results of the discrimination power control strategies that are developed in Chapter 4.

2 Data fusion in military operations

By reducing uncertainty in the existing pieces of information and providing means to infer about the missing pieces, data fusion supports the operators in compiling and analyzing the tactical picture and ultimately improving the situation awareness of the decision makers.

According to Llinas et al. [9], in their revision of the model proposed initially by the US DoD Joint Directors of Laboratories (JDL) sub-panel [8], the data fusion process is subdivided into five levels where each succeeding level deals with a higher level of information abstraction (see Figure 1).

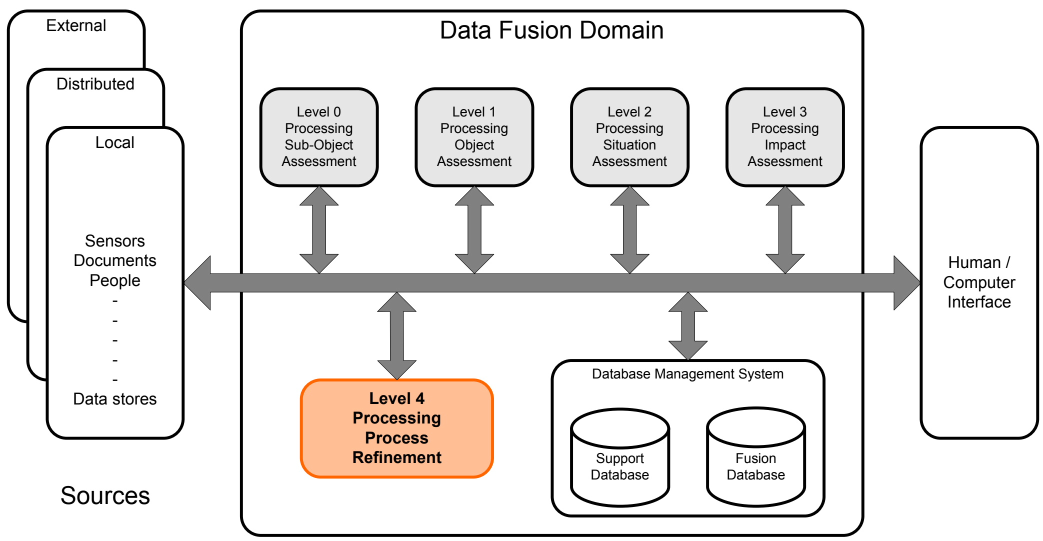


Figure 1: JDL model of data fusion

Level 0 - is the sub-object assessment level and deals with the estimation and prediction of signal/object observable states on the basis of pixel/signal level data association and characterization. This includes the signal detection and feature extraction.

Level 1 - also referred to as the object assessment level, uses the sensor data from Level 0 to optimally estimate the current kinematic properties of the target, and predict their future. It also makes inferences about the target's identity and other key attributes. The output of Level 1 is an aggregated composite tactical picture.

Level 2 - concerns the situation assessment issue and leads to a more symbolic representation of the environment and the relationships among the key entities and the events in it.

Level 3 - At the highest level of data fusion is the impact assessment level, or Level 3, that projects the current situation into the future and infers about the impact of the assessed situation, the vulnerability and the force capabilities.

The data fusion process had often been portrayed as a purely passive and open loop treatment that simply transforms the pieces of information it receives (see Figure 2). The information gathered by the sensing resources undergoes a fusion process without any feedback to the sensors (sensor management) or to the processing (fusion adaptation).

Figure 2 illustrates the fusion process without feedback (*i.e.*, open loop). Normal operating procedures control the sensors and the data they collect is used in the fusion process to arrive at a high level analysis of the situation of interest. There is no formal provision for adjusting the sensing/processing process to achieve higher performance.

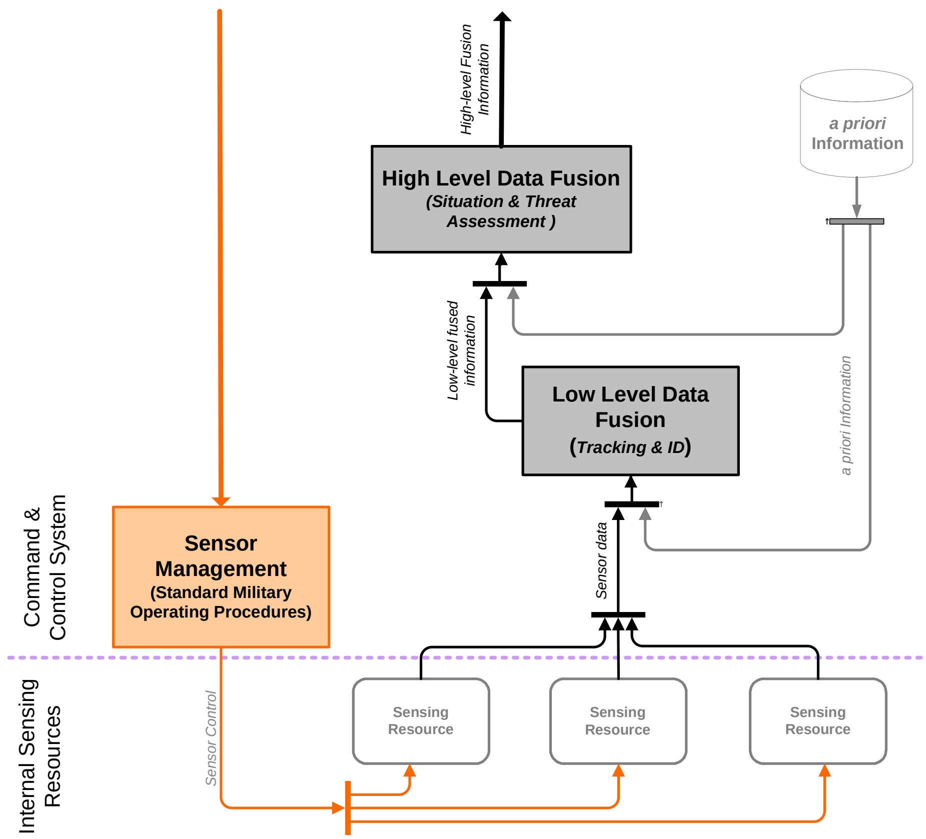


Figure 2: Open-loop data collection and fusion (no adaptation)

However, the effectiveness of an advanced system is not only determined by the capabilities of its individual functionalities and resources alone, but also by the effectiveness of the whole system integration. This integration must focus on a cooperative, synergistic, and efficient utilization of all of the available resources/processing components. Therefore, to gain higher performance, a modern surveillance system needs many additional functions, and the most essential is an active feedback or adaptation (see Figure 3).

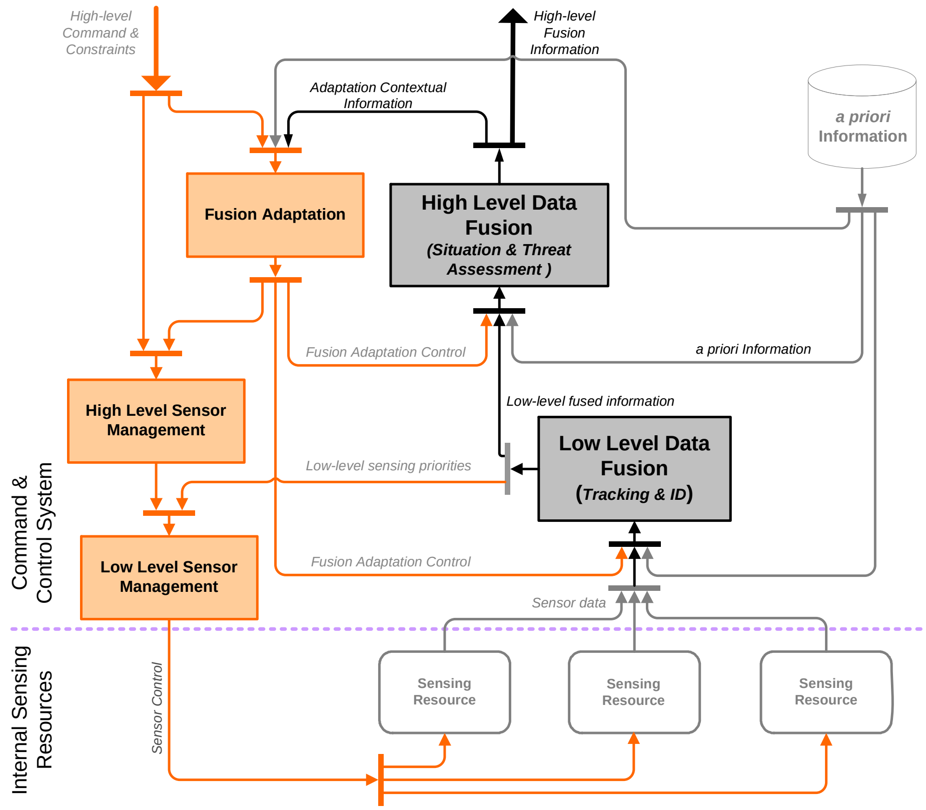


Figure 3: Closed-loop data collection and fusion (with adaptation)

Figure 3 illustrates the fusion process when adaptation and sensor management are used in a feedback-based sensing and processing strategy. To make adjustments to the sensing and processing operations, adaptation and sensor management use outputs from higher fusion processes. This corresponds to the definition and the role of Level 4 of the JDL model. It has to do with how to best manage, coordinate and organize the processing at lower levels and the sensing resources in a manner that synergistically improves the data fusion [14, 15]. Level 4 defines the adaptive data fusion and the related sensor management problems that are treated in the sequel.

2.1 Adaptive data fusion

Generally speaking, a system is called adaptive if it can analyze its own performance and dynamically reconfigure itself to compensate for changes in its context. The changes might be from the environment it evolves in, its objectives and/or its requirements. Instead of being developed for a specific situation, adaptive systems are therefore able to handle a wide class of situations defined by a set of structural constraints on their context. Adaptation in data fusion has been the object of a growing interest during the last few years and is still the least mature of the JDL levels [16, 17, 10]. It is expected that within the data fusion context, the introduction of feedback and adaptation concepts would result in an increased performance. Still, this functionality, which would make all the difference, is often missing in modern data fusion systems. It is worth noting that sensor management represents a major component of the adaptation data fusion problem on which most of the recent research effort has been focused [18, 14, 19].

An adaptive system needs to perceive the environment it operates in and uses this knowledge to produce appropriate actions to achieve its goals [20]. The system must take into account the possible dynamic nature of the environment it interacts with in order to reach its goals throughout a wide range of situations, with the desired level of performance.

Therefore, handling the adaptation problem, in data fusion applications, presumes that the required performance of the data fusion system can be specified quantitatively to define the adaptation goals and objectives. A metric can then be calculated and used to evaluate the data fusion performance (*i.e.*, the deviation from the desired behavior). This allows the adaptive data fusion system to monitor its behavior and detect deviations from commitments or new opportunities. Actions can then be taken to make the system attain its goals with the desired level of performance.

As illustrated by Figure 4, the performance measurement and control process can be performed recursively at different levels of abstraction, where the loop of level $n+1$ sets the objectives for the loop of level n. The latter selects the appropriate actions to achieve those objectives. Associated with each adaptation loop is a performance measure that provides the necessary feedback from the environment.

2.2 Target Tracking

Tracking operations, as part of the situation analysis process, is aimed at providing accurate and timely kinematics, identification, and classification information about the entities within the VOI. This information is referred to as the compiled Tactical Picture (TP). The military typically operates in demanding, dynamic, semi-structured and large-scale environments. This reality makes it difficult to detect, recognize/classify and track accurately all entities within the VOI, thus diminishing the capabilities to react and response properly to the ones that pose actual threat. This can be very critical to own-force survival in high target-density operations, such as in littoral environments.

In this report, target tracking concentrates on kinematics[1], where the sensor data is used to optimally estimate the current kinematical properties of the target and predict their future

[1] Target identification and classification is not part of this work.

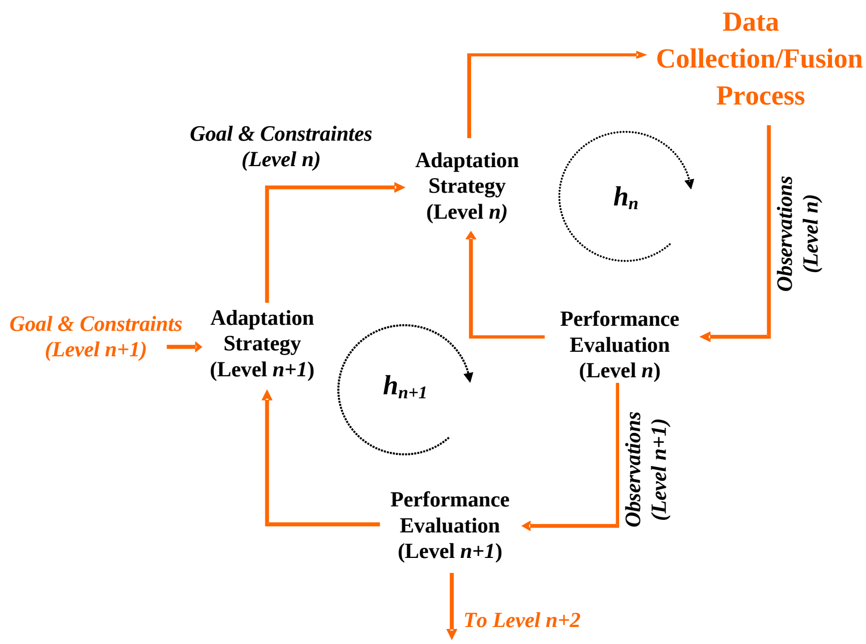


Figure 4: Two-level Cascade Control Loop

positions. A widely used algorithm for estimating time-varying target states is the Kalman filter, which will be described below.

2.2.1 Kalman filtering

For time-varying quantities and for linear and Gaussian-noise systems, the Kalman filter provides optimal state estimation [21, 3]. However, in most applications, there may be some non-linearity that can be associated with the process model, the observation model or with both. In such cases, a modified version of the Kalman Filter known as the Extended Kalman Filter (EKF) must be used [22]. With the EKF, the non-linear functions are linearized approximately using partial derivatives of the non-linear functions, so that the state transition and observation models need not necessarily be linear functions of the state. The following give the equations of the dynamical model and of the EKF used by the underlying tracking algorithm. The discrete-time dynamical model of the targets is given by

$$\boldsymbol{x}_{k+1} = \boldsymbol{f}(\boldsymbol{x}_k) + \boldsymbol{\Gamma}\boldsymbol{v}_k \tag{1}$$

$$\boldsymbol{z}_{k+1} = \boldsymbol{h}(\boldsymbol{x}_{k+1}) + \boldsymbol{w}_{k+1} \tag{2}$$

where $\boldsymbol{x}$ is the n-dimension state vector, $\boldsymbol{v}$ is the process noise with covariance matrix $\boldsymbol{Q}$, $\boldsymbol{z}$ is the measurement vector and $\boldsymbol{w}$ is the measurement noise, whose covariance matrix will be denoted $\boldsymbol{R}$. $\boldsymbol{\Gamma}$ is the discretized continuous time process noise transition matrix. Thus the

EKF will account for both the uncertainties resulting from the process and measurement noises. The time-update equations for the EKF algorithm are given by

$$\hat{x}_{k+1|k} = \boldsymbol{F}_k \hat{x}_k \tag{3}$$

$$\boldsymbol{P}_{k+1|k} = \boldsymbol{F}_k \boldsymbol{P}_k \boldsymbol{F}_k^T + \boldsymbol{\Gamma} \boldsymbol{Q} \boldsymbol{\Gamma}^T \tag{4}$$

where $\boldsymbol{F}_k$ is the Jacobian of $\boldsymbol{f}$. The above-given predicted values are used to calculate the updated version of the state and the corresponding error covariance matrix.

$$\boldsymbol{P}_{k+1|k+1}^{-1} = \boldsymbol{P}_{k+1|k}^{-1} + \boldsymbol{P}_z^{-1} \tag{5}$$

$$\boldsymbol{P}_{k+1|k+1}^{-1} \hat{\boldsymbol{x}}_{k+1|k+1} = \boldsymbol{P}_{k+1|k}^{-1} \hat{\boldsymbol{x}}_{k+1|k} + \boldsymbol{P}_z^{-1} \boldsymbol{z}_{k+1} \tag{6}$$

with

$$\boldsymbol{P}_z^{-1} = \boldsymbol{H}_{k+1}^T \boldsymbol{R}^{-1} H_{k+1} \tag{7}$$

and where $\boldsymbol{H}_k$ is the Jacobian of $\boldsymbol{h}_k$. k represents the discretized time instant.

The next chapters will show how the tracking process can be adapted to control the discrimination power of the tracked targets.

2.2.2 Adaptation in tracking

Adaptation in the specific context of target tracking aims at producing a system that can readily adapt to changing operating environment and needs. An adaptive tracking system must be able to measure and detect changes in its performance index and respond to these changes by performing structural changes. These structural changes may involve the sensing resources as well as the tracking algorithms [20]. Chapter 4 will describe an adaptive tracking strategy where feedback control is applied on sensing resources in order to achieve given tracking objectives.

3 Discrimination power

Discrimination power is defined as the capability to distinguish two or more observed objects. State estimation is at the source of the discrimination power problem. If true states could be obtained instead of estimates, discrimination power would not be an issue. The next paragraphs will discuss the importance of discrimination power in target tracking applications.

A tracking system is mainly characterized by the sensors and the algorithms that process the sensor measurements to provide state estimation of targets. Sensors have two principal characteristics that come into play in the discrimination power problem. These are accuracy and resolution, as illustrated in Figure 5.

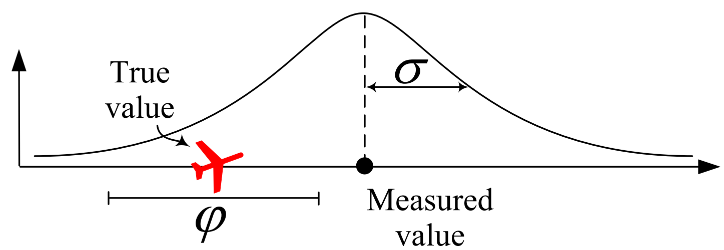


Figure 5: Sensor with accuracy σ (Gaussian probability distribution) and resolution φ

Note that sensor accuracy and estimate accuracy are defined differently. In case of a sensor, the accuracy is defined according to the measurement error probability distribution, which is assumed Gaussian. Practically, the value of accuracy specified in most sensing systems represents the standard deviation of the distribution. On the other hand, the accuracy associated with an estimation represents its uncertainty with respect to the true value. Under the normality assumption, it is given by the standard deviation of the estimate posterior probability distribution function. Equivalently, accuracy can also be expressed as the standard deviation of the estimate's normally distributed random error with 0.0 mean. Note that accuracy is often used to calculate the coverage interval of estimates, that will be discussed in Subsection 3.2.1.2. Furthermore, the resolution of a sensor has to do with its ability to distinguish between objects according to the received signals. For a given sensor, its specified value of resolution is equal to the closest distance for which it can distinguish two objects. Therefore, resolution in itself represents some sort of discrimination power. It expresses discrimination power at the signal level.

Moreover, once measurements and estimates are produced, the capability to distinguish the different observed objects may still be an issue. In such a case, the discrimination power has to do with accuracy rather than resolution. Although accuracy depends on the signal characteristics, it is expressed in terms of the statistical characteristics of the observations, *i.e.* the probability distribution of the true state according to the observations. The discrimination power is then the capability to distinguish between objects according to their statistical characteristics. This capability is directly related to the degree of similarity between the statistical characteristics of the objects. The more the statistics of observed objects are similar, the less is the discrimination power.

According to this, it turns out that resolution and accuracy each relate to a different discrimination power level, that are the signal level and the statistical level, respectively. Figure 6 illustrates each of the two levels with respect to accuracy and sensor resolution.

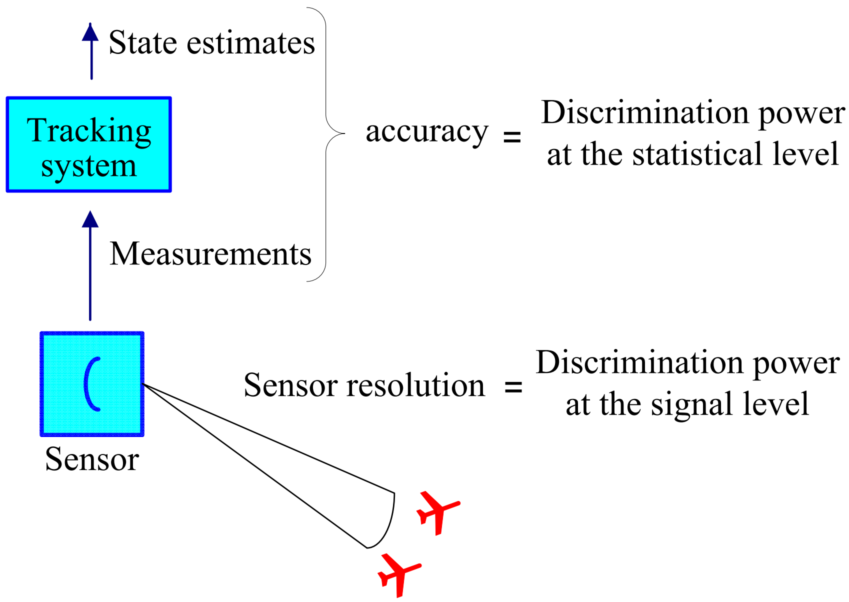
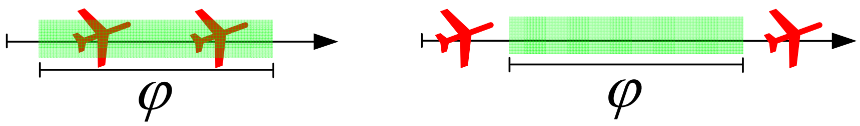


Figure 6: Discrimination power levels

3.1 Signal level discrimination power

As mentioned above, signal level discrimination power is defined as the capability to distinguish two or more objects according to the signals produced by the sensors. Suppose for example, a one-dimensional (1D) sensor that has an accuracy represented by a Gaussian distribution with a standard deviation σ. The sensor also has a resolution φ, which is the minimum separation interval at which two targets can be separated. Given the 1D sensor and two targets in the 1D space, two situations may happen: i) the distance between the two targets is below the sensor resolution, shown in Figure 7 (a), and ii) the distance between the two targets is larger than the sensor resolution, shown in Figure 7 (b).

When the distance between the two targets is below the sensor resolution, the sensor will report only one observed target since it cannot distinguish the two closely spaced targets



(a) Distance between targets is below the sensor resolution φ

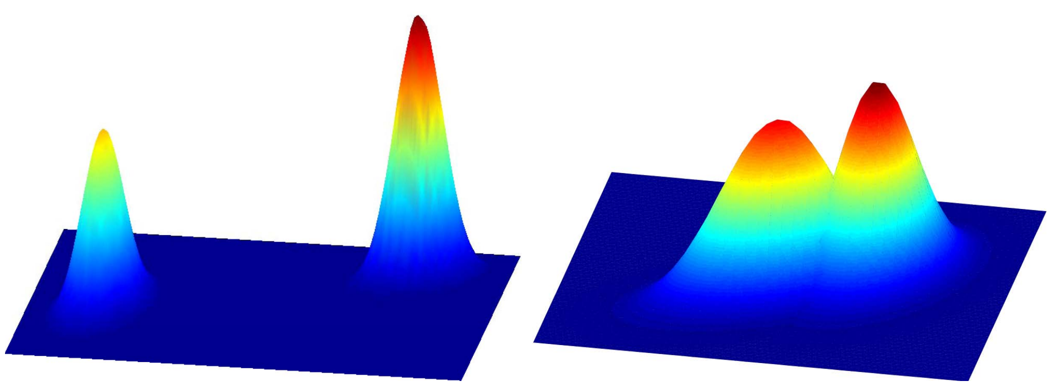
(b) Distance between targets is larger than the sensor resolution φ

Figure 7: Two targets observed in a 1D space

on the received signal. In such a case, the discrimination power problem has to do entirely with signal processing and sensor resolution; thereby only better sensor resolution could improve the discrimination power. Such a problem will not be discussed further in this work.

3.2 Statistical level discrimination power

When the distance between two targets is larger than the sensor resolution (Figure 7 (b)), the sensor will usually report two different target observations. In that case, the sensor has enough discrimination power at the signal level. However, even though a different observation is produced for each of the two targets, there may be a discrimination power problem related to the estimation process, *i.e.* the accuracy of the estimates. As defined in Chapter 6, the accuracy of an estimation depends on the related probability distribution. In case of two or more estimations, the closer the related probability distributions are, the lower will be the discrimination power. This is shown in Figure 8.



(a) High discrimination power - There is almost no overlap between the probability distributions of the estimated states.

(b) Low discrimination power - There is a large overlap between the probability distributions of the estimated states.

Figure 8: Discrimination power for two state estimates

Within the tracking process, filtering, the track updates (*i.e.*, state updates and time updates) presented in Subsection 2.2.1 influence the accuracy of the state estimation, which has a direct impact on the discrimination power over time. In Chapter 4, a method for controlling the discrimination power is presented, where track update periods are adjusted adaptively.

3.2.1 Discrimination power metrics

Any metric derived to measure the discrimination power level will have to be based, in one way or another, on the probability distributions of objects in space and time. Therefore, before deriving such metrics, it is important to recall some basic concepts around the notion of probability.

3.2.1.1 Probability

There exist different interpretations of what probability is about. Generally, statisticians divide into two groups in their approach for interpreting probability, the Bayesians and the frequentists [23, 24, 25, 26, 27][2].

With the Bayesian approach, probability is interpreted as a degree of belief that a parameter will have a given value. The degree of belief is conditional on all relevant information about the parameter. Practically, this assumes a prior distribution for the parameter to estimate. Bayesian statistics are the basis for target tracking algorithms such as Kalman filtering.

Often said to be closer to scientific reasoning [27], the frequentist approach, also called conventional or frequency-based approach, interprets probability as the relative frequency of something happening. Frequentists consider parameter estimation as the result of a repetition of experiments, where an estimated parameter is a random variable that can take on different values when the experiment is repeated. On the other hand, Bayesian statistics do not consider estimation as a repetition of experiments, where an estimated parameter is seen as an unknown variable instead of a random variable.

Depending on the approach, Bayesian or frequentist, measuring the discrimination power may have different meanings. We present two ways of measuring the discrimination power, coverage intervals[3] and Mahalanobis distance. The former refers to the Bayesian approach, while the latter is a frequentist method. The measures consider two estimates at a time for calculating the discrimination power.

[2]Note that R.A. Fisher presented an approach for interpreting statistics that is also popular among the scientific community [28, 29]. In short, his approach consists of a series of theories that offer compromises between the Bayesian and frequentist.

[3]Note that coverage intervals are to the Bayesian approach what confidence intervals are to the frequentist approach.

3.2.1.2 Coverage intervals

A Coverage Interval (CI) is an interval on the probability distribution function associated with the estimated state. It has a different interpretation from the confidence intervals in the frequentist approach [24, 25].

Suppose a state x is estimated from some measurements $Z^k = [z_1, z_2, ..., x_k]$ and that the resulting probability distribution is $N(\hat{x}, \sigma)$. A coverage interval is an interval obtained from the distribution $N(\hat{x}, \sigma)$ that expresses how much the estimated value $\hat{x}$ can at most deviate from the unknown true value x [30]. The interval has an associated probability α that it includes the true value, also called degree of belief. Generally, the recommended degree of belief is $\alpha = 95\%$, which is illustrated in Figure 9 and corresponds to 2 standard deviations (2σ) of the estimated value for a Gaussian distribution [31].

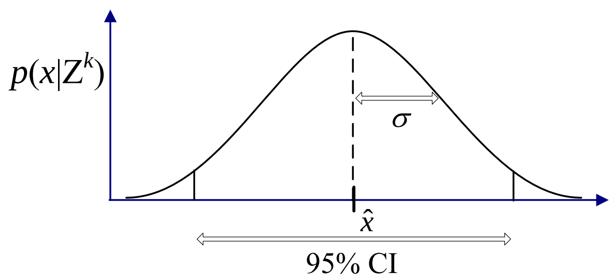


Figure 9: 95% coverage interval (CI) of an estimate $\hat{x}$

Under the Bayesian approach, the interval shown in Figure 9 means that chances are 95% that the true value of x be included in the interval[4].

Considering two different estimates $\hat{x}_1$ and $\hat{x}_2$ from group of measurements Z_1^k and Z_2^k, respectively, the discrimination power will be determined according to their respective CIs, CI_1 and CI_2, for a degree of belief α with

$$CI_1 = [C_1^l, C_1^u] \tag{8}$$

and

$$CI_2 = [C_2^l, C_2^u] \tag{9}$$

and where l stands for "lower limit" and u stands for "upper limit". Thus, when the coverage intervals of two estimates do not overlap, that is

$$[C_1^l, C_1^u] \cap [C_2^l, C_2^u] = \emptyset, \tag{10}$$

[4]With the frequentist approach, the interpretation is that the calculated confidence interval has a 95% probability of containing the true states x. In other words, if confidence intervals were calculated repeatedly with new samples (or measurements), 95% of them would contain the true state x.

it is assumed that there is a statistically significant difference between the estimates $\hat{x}_1$ and $\hat{x}_2$. It is then understood that the two estimated objects can be clearly distinguished and that the discrimination power is fair. This is shown on Figure 10 where $C_1^u = C_2^l$.

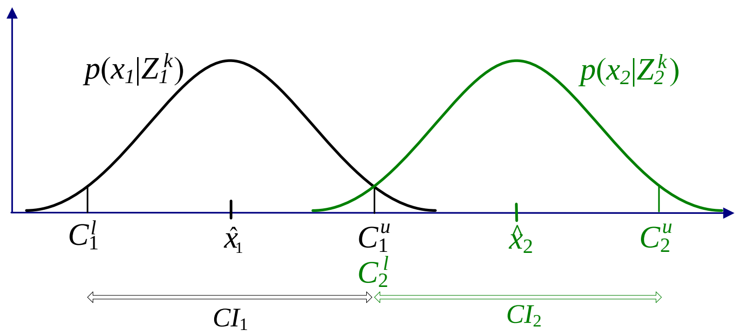


Figure 10: Confidence intervals and discrimination power - CI_1 and CI_2 do not overlap, the discrimination power is fair

On the contrary, when the coverage intervals of two estimates overlap, that is

$$[C_1^l, C_1^u] \cap [C_2^l, C_2^u] \neq \emptyset, \tag{11}$$

the conclusion is that there is not a statistically significant difference between the estimates $\hat{x}_1$ and $\hat{x}_2$. Therefore, the two estimated objects cannot be clearly distinguished and the discrimination power is too low. This is shown on Figure 11, where $C_1^u > C_2^l$. Note that under the frequentist approach, it is not necessarily true that there is not a statistically significant difference between both estimates when the confidence intervals do overlap [32]. Hence this method does not fit with the frequentist viewpoint.

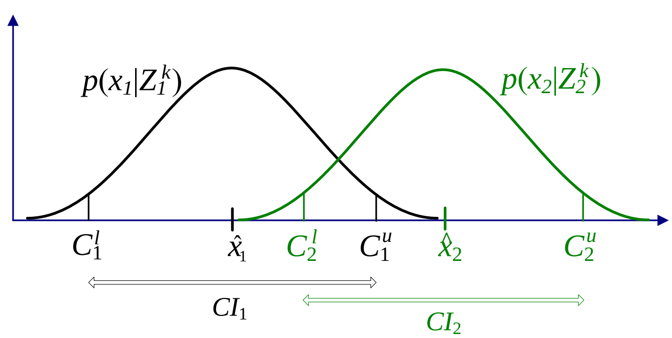


Figure 11: Confidence intervals and discrimination power - CI_1 and CI_2 overlap, the discrimination power is too low.

Although coverage intervals are easy for the 1D case, the method is more complex for the 2D (and more) case. In 2D for example, applying the coverage intervals concept would require calculating intersections of probability distributions contours (ellipsoids for Gaussian distributions). Other methods should then be considered, such as the Mahalanobis distance measure.

3.2.1.3 Mahalanobis distance

The Mahalanobis distance is a statistics that computes a difference between two estimates by taking into account their variances [33]. The Mahalanobis distance d between two estimates $\hat{\boldsymbol{x}}_i$ and $\hat{\boldsymbol{x}}_j$ is defined as.

$$d(\hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_j) = \left[\hat{\boldsymbol{x}}_i - \hat{\boldsymbol{x}}_j\right]^T \left[\boldsymbol{P}_i + \boldsymbol{P}_j\right]^{-1} \left[\hat{\boldsymbol{x}}_i - \hat{\boldsymbol{x}}_j\right] \tag{12}$$

where $\boldsymbol{P}_i$ and $\boldsymbol{P}_j$ are the covariance matrices for the state estimates $\hat{\boldsymbol{x}}_i$ and $\hat{\boldsymbol{x}}_j$, respectively. Because of the Gaussian assumption, $d(\hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_j)$ is a χ^2 random variable with n_d degrees of freedom, where n_d is the number of dimensions for the state estimates $\hat{\boldsymbol{x}}_i$ and $\hat{\boldsymbol{x}}_j$.

For N estimates, the distances for each possible pair of estimates are represented in the $N \times N$ dissimilarity matrix

$$\mathcal{D} = \left[d(\hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_j)\right] \tag{13}$$

The Mahalanobis distance can be used as a measure of the similarity between tracks. Figure 12 illustrates pairs of tracks' estimates with different levels of similarity, represented by the statistical distance d.

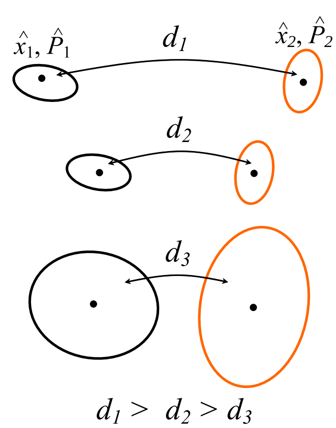


Figure 12: Statistical distance d as a track dissimilarity metric

The ellipsoids represent contours of constant probability for the two-dimension and normally distributed position estimates of the tracks. As can be seen in Figure 12, the farther the position estimates $\hat{\boldsymbol{x}}_1$ and $\hat{\boldsymbol{x}}_2$ are from each other in the space, the higher are the Mahalanobis distance and track dissimilarity ($d_1 > d_2$). Also, the smaller the estimation error covariance matrices $\boldsymbol{P}_1$ and $\boldsymbol{P}_2$ are, the higher are the Mahalanobis distance and track dissimilarity is ($d_2 > d_3$).

3.2.1.4 χ^2 test for assessing discrimination power

Furthermore, given the Mahalanobis distance, how would one determine whether the discrimination power is fair or not? To answer this question, let us consider the following hypotheses for the two estimates $\hat{\boldsymbol{x}}_i$ and $\hat{\boldsymbol{x}}_j$:

$\boldsymbol{H}_0$: $\hat{\boldsymbol{x}}_i$ and $\hat{\boldsymbol{x}}_j$ refer to the same object. This hypothesis suggests that the discrimination power is not high enough.

$\boldsymbol{H}_1$: This is the alternative hypothesis that $\hat{\boldsymbol{x}}_i$ and $\hat{\boldsymbol{x}}_j$ refer to different objects. This hypothesis suggests that the discrimination power is sufficiently high.

Statistically, testing hypothesis $\boldsymbol{H}_0$ against $\boldsymbol{H}_1$ comes down to determine whether estimates $\hat{\boldsymbol{x}}_i$ and $\hat{\boldsymbol{x}}_j$ come from the same distribution or not. The Mahalanobis distance evaluated in Equation 12 is used to determine whether $\boldsymbol{H}_0$ should be rejected (and replaced with $\boldsymbol{H}_1$) or not. The criterion for deciding between $\boldsymbol{H}_0$ or $\boldsymbol{H}_1$ will be:

$$\text{if} \quad d(\hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_j) \leq \chi^2_{(\alpha,n_d)}, \quad \text{Accept } \boldsymbol{H}_0 \tag{14}$$

$$\text{if} \quad d(\hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_j) > \chi^2_{(\alpha,n_d)}, \quad \text{Reject } \boldsymbol{H}_0 \text{ and accept } \boldsymbol{H}_1 \tag{15}$$

where $\chi^2_{(\alpha,n_d)}$ is the chi-square percent point function with nd degrees of freedom and a significance level of α. The significance level α represents the confidence in hypothesis $\boldsymbol{H}_0$ [34, 35]. That is, if $\boldsymbol{H}_0$ is true, there should be a 1-α probability that $d(\hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_j) < \chi^2_{(\alpha,n_d)}$. Thus, the lower the significance level α, the higher the confidence should be about accepting or rejecting $\boldsymbol{H}_0$. In terms of discrimination power, this significance level α represents a measure of the degree of discrimination power. As α decreases, the corresponding expected discrimination power level increases.

Based on the definition of discrimination power presented in the current chapter, the next chapter proposes an approach to control, adaptively, the discrimination power over a certain volume of interest.

4 Discrimination power control

This chapter discusses the problem of controlling the discrimination power, at the statistical level, in a tracking system. The goal is to maximize the discrimination power of the tracks in a certain volume of interest, such that all tracks can be clearly distinguished. This work concentrates on controlling the discrimination power by adjusting track update periods, that represent time intervals between sensor measurements.

First, a simple algorithm for adaptively updating tracks is presented in Section 4.1. Then, a clustering-based control method, that is better suited for target tracking systems, is presented in Section 4.2.

4.1 Simple track update algorithm

A solution to control the track dissimilarity (and the related discrimination power) consists in adjusting adaptively the time intervals between updates for the different tracks. The time interval between measure updates will also be referred to as the update period. It has a significant influence on the variation in time of the track accuracy (*i.e.*, covariance matrix). Shorter periods between updates should yield higher track accuracy and therefore higher dissimilarity between tracks.

Therefore, the goal of an adaptive tracking system is to choose appropriate update periods for each track in order to keep a certain level of discrimination level within the volume of interest.

A straightforward discrimination power control solution is to have each track's own update period h be a function of the distance with its nearest neighbor, according to the Mahalanobis distance. A track i would have an update period h_i determined such that

$$h_i = \zeta\left[\min_k d(\hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_k)\right], \quad k \in 1, ..., N \tag{16}$$

where $d(\hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_j)$ is as defined by Equation 12 and ζ is a function that expresses the relation between h and d.

Resolving Equation 16 would be complicated practically, requiring a lot of computations. Furthermore, the resulting strategy could hardly match with the scheduling of sensors.

4.2 Clustering-based control method

The clustering-based method aims at separating the volume of interest into regions having different discrimination power levels. The tracks in each region are then updated at some frequencies that will help enhance the discrimination power in regions where the latter is low. The method relies on an adaptive control structure suited for the specific problem of target tracking and depicted in Figure 13. It is a practical implementation of the adaptive data fusion concepts presented in Section 2.1 and illustrated in Figure 4.

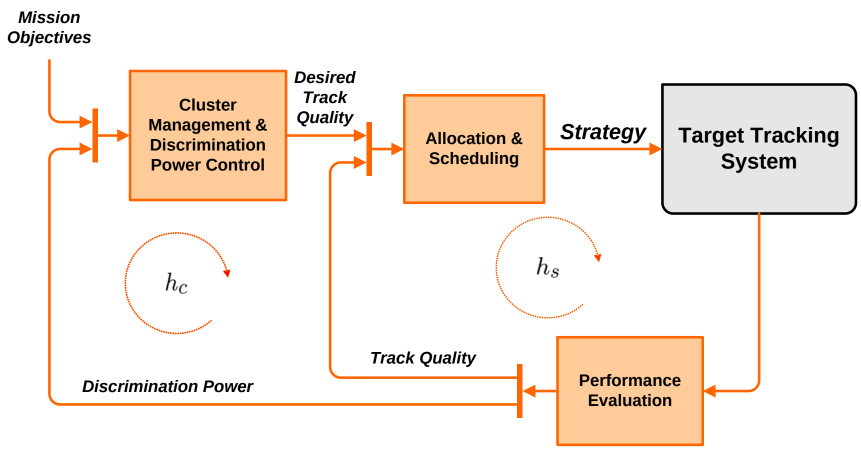


Figure 13: Clustering/discrimination power-based Two-Level Control Loop

The control structure is made of a two-level cascade control loop. Its two loops operate at two different time-scales, with the following objectives

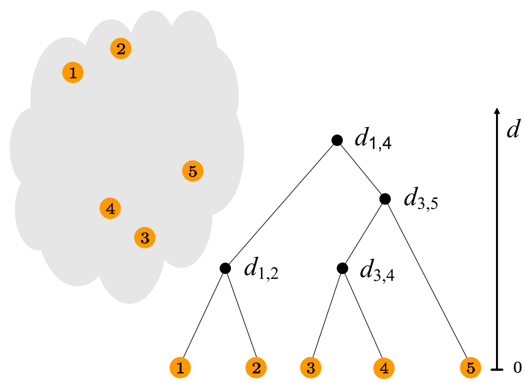
- **Outer-loop** – The characterization of the whole volume of interest based on the concept of discrimination power, where distinct regions are created and managed dynamically based on the targets spatial distribution and by using clustering techniques. To ensure a certain level of cluster persistence, this loop operates at low frequency, as defined by the basic period $h_c > h_s$ in Figure 13. Thus sensor scheduling can be made by considering several sampling intervals.

- **Inner-loop** – The adaptive control of discrimination power over the volume of interest, by the appropriate selection of the track update frequency and sensor scheduling within each distinct region. This adaptation loop operates at a faster time scale than the outer loop ($h_s < h_c$). Note that the minimal value for h_s is a characteristic of the sensors.

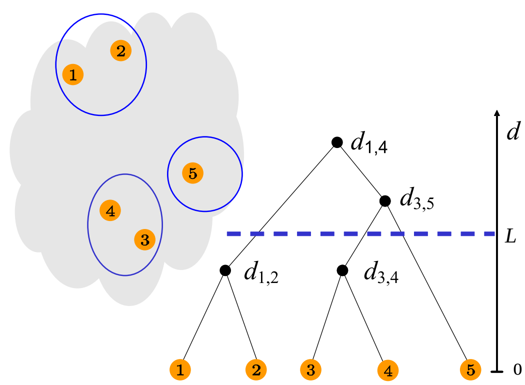
4.2.1 Hierarchical clustering of tracks

When regions of the VOI are to be considered for controlling sensor scans, separating tracks into clusters can provide a way to determine the desired update strategy. Clusters of targets represent different regions of the space with different discrimination power levels.

Agglomerative hierarchical clustering [33] is suitable for controlling the discrimination power using the region-based approach. With agglomerative hierarchical clustering, a binary tree is constructed based on a linkage measure, where each leaf represents the predicted state estimate of a track (Figure 14). The linkage measure is determined and related to the type of hierarchical clustering algorithm.



(a) Distance Tree



(b) Threshold and clusters

Figure 14: Distance tree and hierarchical formation of clusters

A hierarchical cluster tree is created based on the dissimilarity matrix $\mathcal{D}$. The process of hierarchical clustering is as follows:

1. Assign each track to a cluster to have N clusters.

2. Merge the closest pair of clusters, where cluster C_i and C_j are merged together to result in $N-1$ clusters.

3. Compute distances between the new cluster and each of the old clusters. The distance computation depends on the type of clustering used. The following gives, for two clusters C_i and C_j, the resulting distances $d_{min}(C_i, C_j)$ and $d_{max}(C_i, C_j)$, when single-

linkage and complete-linkage are used, respectively

$$d_{min}(C_i, C_j) = \min_{\hat{x} \in C_i, \hat{x}' \in C_j} d(\hat{x}, \hat{x}') \quad (17)$$

$$d_{max}(C_i, C_j) = \max_{\hat{x} \in C_i, \hat{x}' \in C_j} d(\hat{x}, \hat{x}') \quad (18)$$

4. Repeat Steps 2 and 3 until all tracks are clustered into a single cluster of size N.

The single-linkage algorithm produces a binary tree where the highest nodes in the hierarchy have the largest distance values. A threshold L applied on the distances allows to group tracks into regions. The value of the threshold determines how the tree is separated. All nodes that are below the threshold will have their corresponding tracks regrouped into the same cluster. Each cluster of tracks occupies a particular region of the space. The value of the threshold should depend on the problem at hand, that is the number of targets and their properties, the number of sensors and their properties and most importantly the applications that exploits the results of the target tracking process[5].

4.2.2 Sensor scheduling heuristics

Once the clusters of targets are determined, the scheduling of the sensors is required. Here, a single sensor is considered. It is assumed that the sensor can be allocated to one cluster at a time. It is also assumed that the sensor can be directed instantaneously, without extra cost.

Let R_n be the region occupied by cluster C_n, for which the discrimination power d_n and the track similarity s_n are defined as follows

$$s_n = \min_{i,j} d(\hat{\boldsymbol{x}}_i(k), \hat{\boldsymbol{x}}_j(k)), \quad \hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_j \in R_n \quad (19)$$

$$d_n = s_n^{-1} \quad (20)$$

The two metrics d_n and s_n will be used to define the optimal track update frequency and the scheduling strategy. The update cycle length of the clusters is defined as

$$\begin{aligned} h_c &= h_s \xi \psi && (21)\\ &= h_s \xi \sum_{n=1}^{K} \eta_n && (22)\\ &= h_s \xi \sum_{n=1}^{K} \lfloor \frac{d_n^{-1}}{\min_{i \in \{1,\ldots,K\}} d_i^{-1}} \rfloor && (23)\\ &= h_s \xi \sum_{n=1}^{K} \lfloor \frac{s_n}{\min_{i \in \{1,\ldots,K\}} s_i} \rfloor && (24) \end{aligned}$$

[5] *e.g.*, surveillance, target engagement, or other.

where K is the number of clusters and ξ is an integer defined arbitrarily. The integers η_n define the number of updates that will be performed for each region within a single update cycle ψ. The latter is defined such that the tracks within the cluster that has the highest discrimination power (*i.e.*, smallest s_n) will be updated only once, while the tracks within the other clusters will be more than once.

It is assumed that the sensor has to spend a minimum time t_s over a region to report a contact. This defines a maximum report frequency f_s. The update frequency for each cluster, as function of the sensor frequency f_s, is defined as follows,

$$f_n = \xi^{-1}\psi^{-1}\eta_n f_s \tag{25}$$

For regions that require more than one update, different update scheduling strategies may be possible. Three different scheduling algorithms are considered and compared in the sequel. These are: time-slice, minimum intra-cluster discrimination power and round-robin.

4.2.2.1 Time-slice

This strategy is described by Algorithm 1, where the objective is to separate (in time) the updates of the same region as much as possible in order to maintain a best quality of track with the same number of updates, as illustrated in Figure 15. The schedule period length corresponds to the cluster update cycle length h_c.

procedure TIMESLICE
    $S \leftarrow$ schedule vector of size ψ ▷ Update cycle length
    $j \leftarrow k \mid \eta_k = \max_{l\in\{1,\ldots,K\}} \eta_l$
    $i \leftarrow 1$
    while $\max_{l\in\{1,\ldots,K\}} \eta_l > 0$ **do**
        $S(i) \leftarrow j$
        $\eta_k \leftarrow \eta_k - 1$
        if $\eta_k > 1$ **then**
            $S(\psi - i + 1) \leftarrow j$
            $\eta_k \leftarrow \eta_k - 1$
        end if
        $i \leftarrow i + 1$
        $j \leftarrow k \mid \eta_k = \max_{l\in\{1,\ldots,K\}} \eta_l$
    end while
end procedure

Algorithm 1: Time-Slice Scheduling Strategy

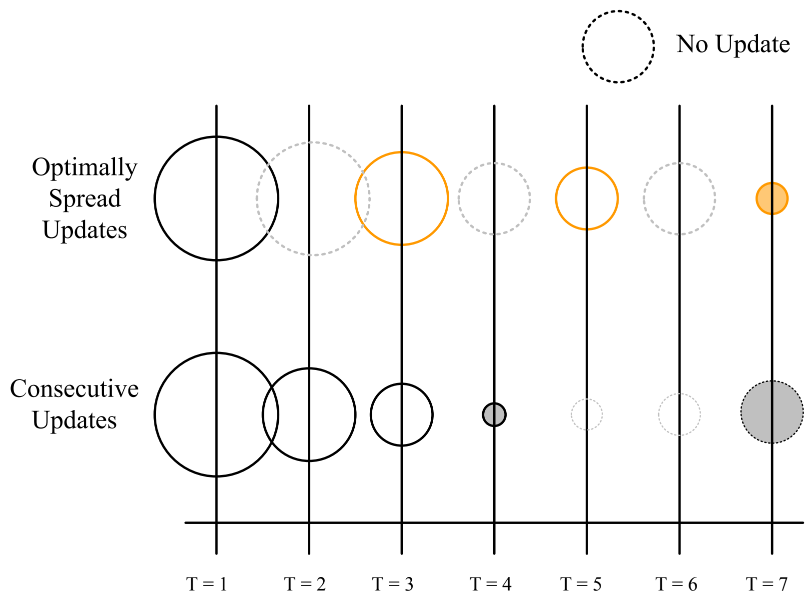


Figure 15: Track Quality as function of scheduling strategy for the same number of updates

4.2.2.2 Minimum Intra-Cluster Discrimination Power (MICDP)

With the minimum intra-cluster discrimination power scheduling algorithm, the next region R_m to be updated is the one with the minimum discrimination power:

$$m \mid d_m = \min_{n \in \{1,\ldots,K\}} d_n \tag{26}$$

where the clusters are being updated after each sensor update, that is

$$h_c = h_s \tag{27}$$

4.2.2.3 Round-robin

The round-robin scheduling strategy updates all the clusters equally. With such a strategy, a cluster that has just been updated will not be updated again until all other clusters have been updated. The update cycle length of the clusters is the same as for the time-slice strategy defined in Equation 24. The round-robin strategy represents the open-loop and static approach for controlling the sensing operations.

5 Results and Discussion

Several scenarios, in which a single (phased array-like) sensor [36] has to track several targets, were simulated. For each of the scenarios, different scheduling strategies were compared on the base of different performance measures. The following sections describe the two-dimension phased array radar model and the performance measures that are used in the simulation in order to test and compare the different scheduling strategies.

5.1 Sensor Model

The sensor model assumes an active sensor that has the capability to switch the direction of its beam instantaneously without inertia. Precisely, the sensor has the following characteristics:

1. The sensor measures range and azimuth.
2. The beam width in elevation is considered large enough to cover the entire elevation span. Therefore, this is a 2D sensor.
3. The beam direction is controllable in azimuth.
4. Measures are made instantaneously. Hence, the search time for a track update is zero.
5. Detection probability is 100%.
6. False alarm probability is 0%.
7. In some cases, it is assumed, for simplicity, that more than one measure on different targets can be made simultaneously. That is, all targets pertaining to a same cluster are updated instantaneously.
8. Standard deviations of range and azimuth measurements are assumed constant. They are $55.6m$ and $\pi/90$ rad (or $0.5°$) in range and azimuth, respectively.

5.2 Performance measures

To evaluate the performance of the proposed solution, several metrics have been defined. They are all function of the uncertainty, as expressed by the error covariance matrix of each state estimate. A sub-set of these metrics is described below.

5.2.1 Discrimination Conflict

We assume that there is a Discrimination Conflict (DC) between two different state estimates $\hat{\boldsymbol{x}}_i$ and $\hat{\boldsymbol{x}}_j$, at time k, if their Mahalanobis distance [33] is lower than (or equal to) a certain threshold λ_d, that is

$$DC_{i,j}(k) = \begin{cases} 1 & \text{if} \quad (\hat{\boldsymbol{x}}_i(k), \hat{\boldsymbol{x}}_j(k)) \leq \lambda_d \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

Thus, there is a discrimination conflict if the overlap between the spatial probability distributions of two targets exceeds some threshold value.

Discrimination conflicts should stay as low as possible to avoid problems with contact/track correlation, target identification and classification. The total number of discrimination conflicts of a tracking system over a period of time $[1, ..., M]$ is the sum of the conflicts for each discrete time steps k:

$$DC_{1,...,M} = \sum_{k=1}^{M} \sum_{j>i} DC_{i,j}(k), \quad i, j \in 1, ..., N \tag{29}$$

5.2.2 Average track-to-track Mahalanobis distance

The average Mahalanobis distance for any pairs of tracks within a given cluster, at a given time k, is defined as

$$AM(k) = \frac{2}{N(N-1)} \sum_{j>i} d(\hat{\boldsymbol{x}}_i, \hat{\boldsymbol{x}}_j), \quad i, j \in 1, ..., N \tag{30}$$

This metrics is a characteristic of the clusters. The higher is the average track-to-track Mahalanobis distance, the better is the discrimination power within the clusters.

5.2.3 Average error covariance matrix determinant

The average error covariance matrix determinant at a time k is defined as

$$ADET(k) = \frac{1}{N} \sum_{i=1}^{N} |\boldsymbol{P}_i(k)| \tag{31}$$

This measure provides a means to express the overall (for the all volume of interest) uncertainty of the tracks at a specific time.

5.3 Scenarios

Three scenarios (A,B,C) are simulated and the three metrics defined above are used to evaluate the performance of the proposed solution. Scenarios A and B feature pre-scripted trajectories of four (4) and seven (7) targets, respectively, while Scenario C uses fifteen (15) randomly distributed targets.

The goal of the control loop for the following scenarios is to maintain the appropriate dissimilarity level between the tracks' latest estimates. The control strategy should make the sensor spend more time over those regions where targets have low dissimilarity.

The Euclidian distance threshold for creating clusters is

$$L = 400m \tag{32}$$

The Mahalanobis distance threshold for calculating the total number of discrimination conflicts is

$$\lambda_d = 50 \text{ m} \tag{33}$$

where λ_d corresponds to the $\chi^2_{(\alpha,nd)}$ value discussed in Sub-section 3.2.1.4. The update cycle length of the clusters h_c and the track update period h_s are 1.0 s and 0.1 s respectively.

The targets move with an assumed constant velocity model. The process noise $\boldsymbol{v}_k$ defined in Equation 1 is white with zero-mean and has a covariance

$$\boldsymbol{E}(\boldsymbol{v}_k \boldsymbol{v}_k') = q\boldsymbol{\Gamma}\boldsymbol{\Gamma}^T \tag{34}$$

with

$$q = 625m^2/s^3 \tag{35}$$

and where

$$\boldsymbol{\Gamma} = \begin{bmatrix} h^2/2 & 0 \\ 0 & h^2/2 \\ h & 0 \\ 0 & h \end{bmatrix} \tag{36}$$

for a time interval $h = t_{k+1} - t_k$. The state transition matrix $\boldsymbol{F}_k$ for the same time interval h is

$$\boldsymbol{F}_k = \begin{bmatrix} 1 & 0 & h & 0 \\ 0 & 1 & 0 & h \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{37}$$

The phased array radar measurements are converted to Cartesian coordinates using the conventional coordinate transformation [3, 37].

5.3.1 Scenario A

To illustrate the benefits of the discrimination power control strategy, a simple scenario with only four (4) targets has been simulated, where two of the four targets cross each other at a given time. Figure 16 illustrates the trajectories of the 4 targets. Targets 1 and 2 are set to cross at about 5 s, while targets 3 and 4 are set far from each other. Following this scenario, it is expected that the tracking system will have more difficulty discriminating Target 1 and Target 2 during their intersection period.

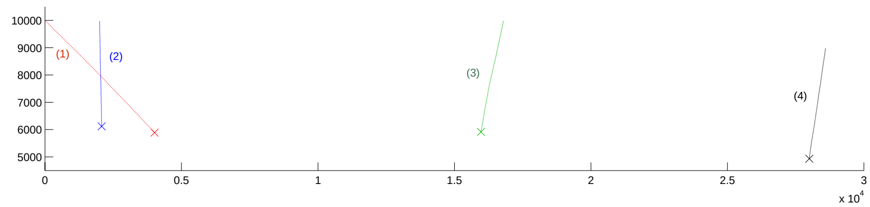


Figure 16: Trajectories of the 4 targets in Scenario A ('X' is the final position)

Figure 17 shows the dissimilarity of the tracks corresponding to Target 1 and Target 2. The dissimilarity is expressed by the Mahalanobis distance[6]. The Mahalanobis distance is shown for the first 8 seconds of the simulation and the different scheduling strategies presented in Sub-sections 4.2.2.1, 4.2.2.2 and 4.2.2.3. For the period of time where targets 1 and 2 are close to each other, that is between about 3 s and 7 s from the start of the simulation, the Mahalanobis distance gets smaller and reaches a minimum at 5 s, that is when targets 1 and 2 are crossing. As illustrated on Figure 17, the time-slice scheduling strategy is the one that was able to obtain the best discrimination power by maintaining the highest Mahalanobis distance, compared to the minimum intra-cluster discrimination power (MICDP) and round-robin scheduling strategies.

5.3.2 Scenario B

A scenario with seven (7) targets has been simulated and the results are presented in this section. Within the considered configuration, certain targets will come too close, at given time instants, to be clearly distinguishable from each other, *e.g.* Target 1 and Target 2 at 5 s, and Target 1 and Target 3 at 14 s, as shown on Table 1 where the closest pairs of targets are given in terms of different simulation times.

Figures 18 and 19 present and compare the resulting track quality based on two different track update strategies, for a tracking duration of 20 s. Dashed ellipses give initial position

[6] Note that any well-defined distance on $\mathbb{R}^n$ may be used as a proximity metric. The presented results and the underlying development are based on the Mahalanobis distance since it considers the error covariances.

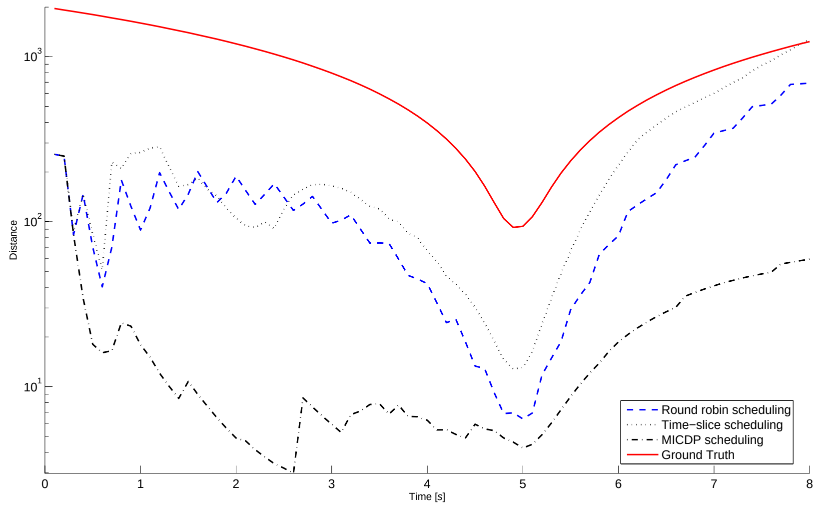


Figure 17: Mahalanobis distance between tracks of targets 1 and 2. The ground truth distance for targets 1 and 2 is also illustrated.

Time (s)	Closest pair	Distance (m)
0	1 - 2	1300
5	1 - 2	10
10	1 - 3	1400
14	1 - 3	5
20	1 - 4	1100

Table 1: Closest pairs of targets in scenario B.

and uncertainty for each target. Plain ellipses are represented only to show final position and uncertainty for each target, and also where discrimination problems are expected, *e.g.*, intersections (Target 1 [red], Target 3 [green]) and (Target 1 [red], Target 2 [blue]).

In Figure 18, a round-robin update strategy was used, where the different clusters of tracks are being allotted the same attention without consideration of any additional information. On the contrary, Figure 19 presents the time-slice strategy, the objective of which is the control of the discrimination power within the different clusters. More attention is paid to critical areas, *i.e.*, where discrimination power tends towards zero. Clusters are created dynamically based on spatial proximity, and the update strategy is defined based on the track dissimilarity in each cluster.

Figure 19 shows clearly the superiority of the time-slice discrimination power control-based scheduling approach over the static round-robin scheduling strategy. Discrimination power is adaptively improved where required, *e.g.*, over intersections (Target 1 [red], Target 3 [green]) and (Target 1 [red], Target 2 [blue]), by increasing the update rate over the clusters created by the targets proximity. Targets that do not need high discrimination power will belong to distinct clusters that will be updated less frequently, *e.g.*, Target 6 [cyan] and Target 5 [yellow]. For the least frequently updated tracks by the adaptive strategy (*i.e.*, Target 3 [cyan] and Target 4 [yellow]), the obtained results show 1.32 km^2 vs. 1.0 km^2 with static for Target 6 [cyan] and 1.11 km^2 vs. .86 km^2 with static for Target 5 [yellow].

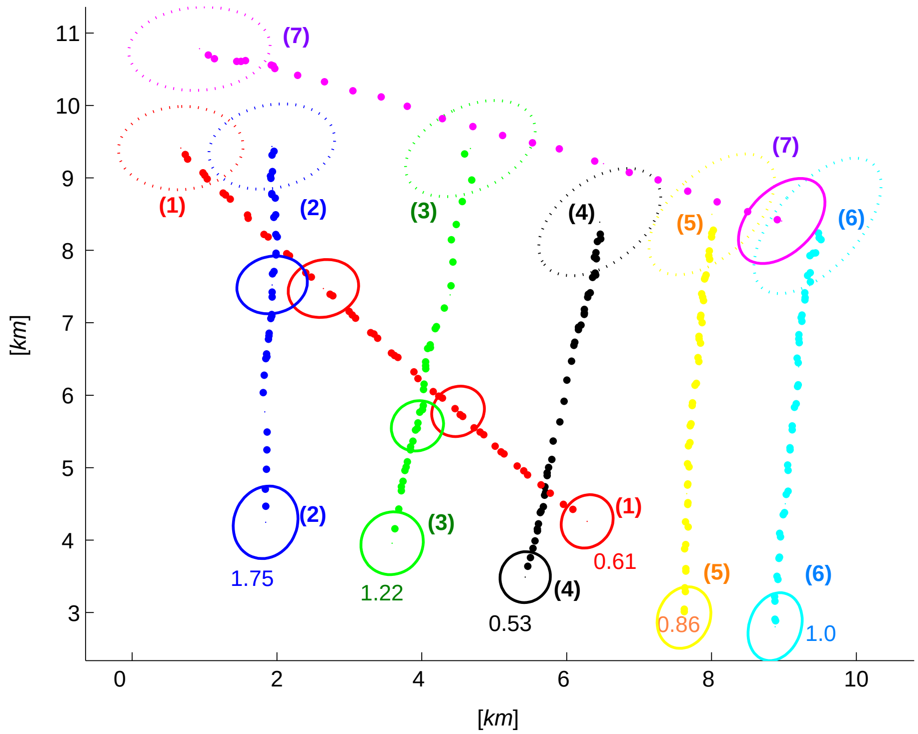


Figure 18: Track quality yielded by round-robin scheduling strategy

Note that, in Figures 18 and 19, the ellipses that are not centered on the last update correspond to tracks to which sensor time was not allocated during the last part of the scenario. For these tracks, only prediction (dead reckoning) is used.

5.3.3 Scenario C

To further evaluate the performance of the proposed strategy, a second scenario with fifteen (15) randomly distributed targets is used. For both axes X and Y in the Cartesian plane, the target initial positions are bounded between $[1000km, 3000km]$. The target initial velocities are determined randomly in the range [0 m/s,250 m/s] over axis X and are set to 0 over axis Y. These give the initial velocity values that may change during the simulation because of a deliberately added noise (see Figure 20). The simulation duration is 15 s.

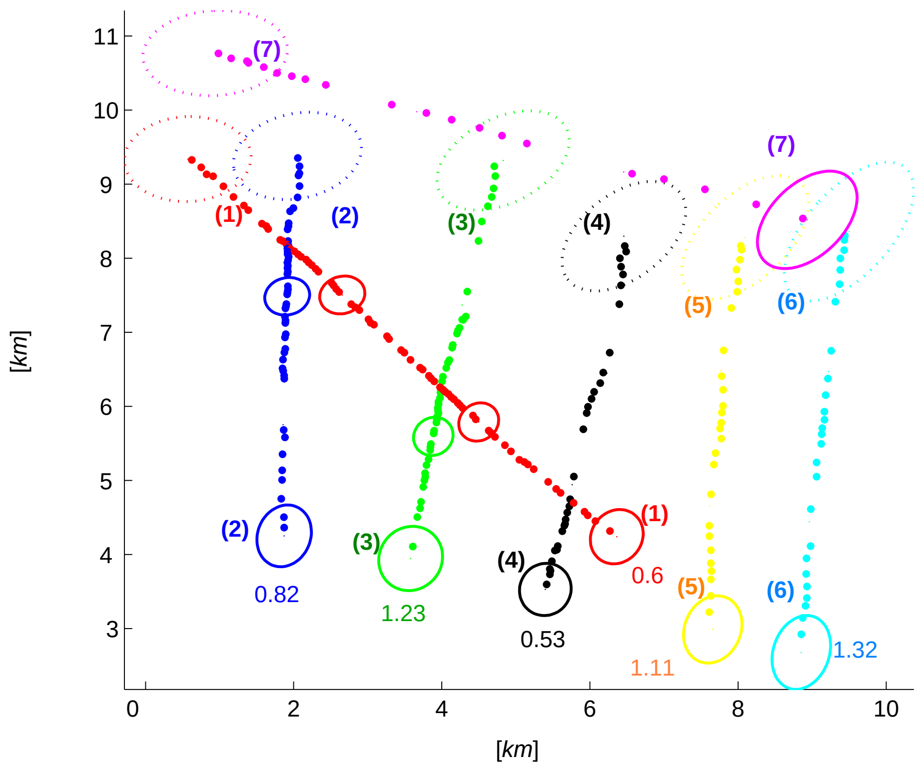


Figure 19: Track quality yielded by the time-slice discrimination power control-based scheduling strategy

An example of the fifteen target trajectories is illustrated in Figure 20. Time-slice, minimum intra-cluster discrimination power (MICDP) and round-robin scheduling strategies were tested. Figures 21 to 24 show the resulting performance measures according to 100 Monte Carlo runs for each of the three scheduling strategies.

The number of clusters, averaged over the 100 Monte Carlo runs, is given in Figure 21. Thus, on average the number of clusters is initially around 7 and increases slightly with time. Such an increase is caused by target dispersion as time goes on.

The average track-to-track Mahalanobis distance (AM) is given in Figure 22. It shows that the highest AM is obtained with the time-slice scheduling strategy. The latter allows maintaining the highest discrimination power over the volume of interest. The MICDP strategy performs worse than the round-robin method and yields the lowest AM.

Moreover, time-slice scheduling provides also the best result when it comes to minimizing the total number of discrimination conflicts, as shown in Figure 23. The latter illustrates the distribution of the total number of discrimination conflicts ($DC_{[1,\ldots,15]}$) over the 100 Monte Carlo runs. Discrimination conflicts occur much more often with the MICDP scheduling

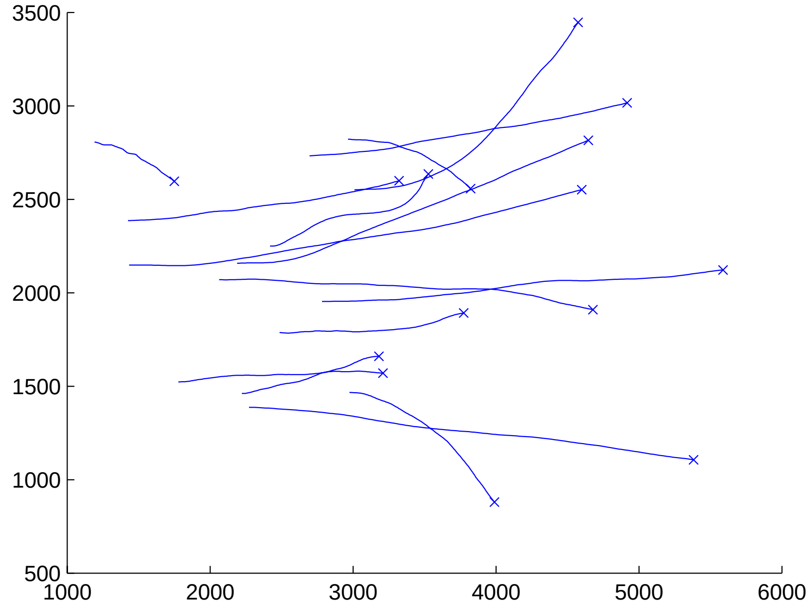


Figure 20: Sample of trajectories of the fifteen targets in Scenario C ('X' is the final position)

strategy, whose average total number of similarity conflicts is 2017, compared to 1400 and 623 for the round-robin and time-slice scheduling methods, respectively. In Figure 23, the lower and upper lines of the box are the 25^{th} and 75^{th} percentiles of the samples. The line in the middle of the box is the sample median. The lines extending above and below the box show the extent of the rest of the samples.

Figure 24 shows that maintaining high discrimination power does not necessarily mean maintaining an overall low individual track uncertainty. It represents the time evolution of the average determinant of the error covariance matrix ($ADET$). It is clearly shown that though time-slice is the best scheduling strategy for maintaining high discrimination power, it is not necessarily the method that maintains the lowest individual track uncertainties overall. For example, between 1 s and 4 s on Figure 24, round-robin scheduling provides a lower $ADET$ than time-slice scheduling over the 100 Monte Carlo runs.

Although both time-slice and MICDP aim at maximizing the discrimination power, the results have demonstrated that time-slice scheduling performs better. The latter focuses the sensing effort where and when required. It also use a more optimized repartition over the cycle of the updates, as given by Algorithm 1.

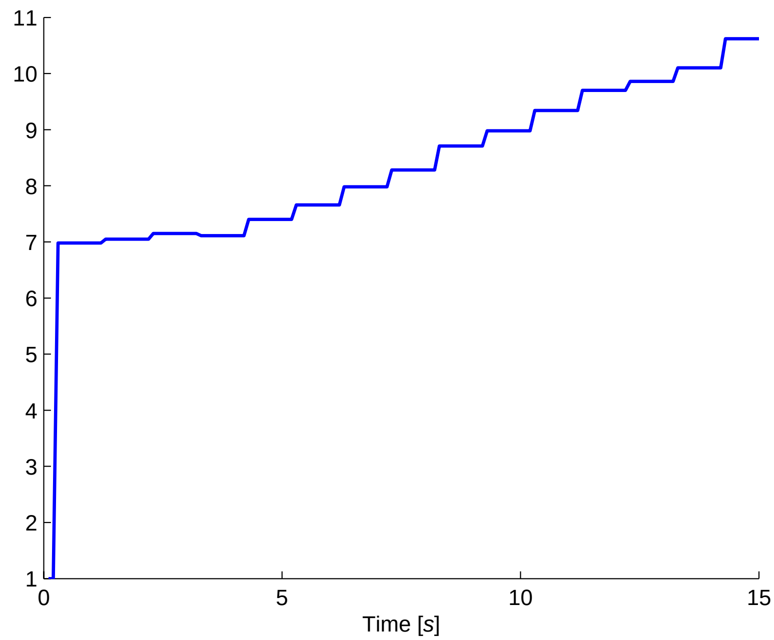


Figure 21: Number of clusters in terms of time

5.4 Notes on clustering and scheduling

The clustering and scheduling algorithms rely on some parameters that must be set properly in order that our adaptive tracking system performs well. The main parameters that are concerned with the performance of the tracking system are:

1. the Euclidian distance threshold L for creating clusters,
2. the cluster update cycle length h_c, and
3. the schedule period length ψ of the time-slice and round-robin scheduling strategies.

Note that, in this report, h_c and ψ are equal. For the results presented in this chapter, L, h_c and ψ were set arbitrarily to provide good performance with the three scenarios. However, in practice an adaptive tracking system would require L, h_c and ψ to be adjusted continually and based on the situation at hand (*i.e.*, the state of the observed targets). From the above results, we already know that ψ should increase as the number of targets increases, such that all targets be included at least once in each update schedule. Also, L should depend on the targets' distribution and on the sensor characteristics. For example, if for a particular application it is given that the observed targets tend to be very close in space and that the sensor is very accurate, then L should be set low.

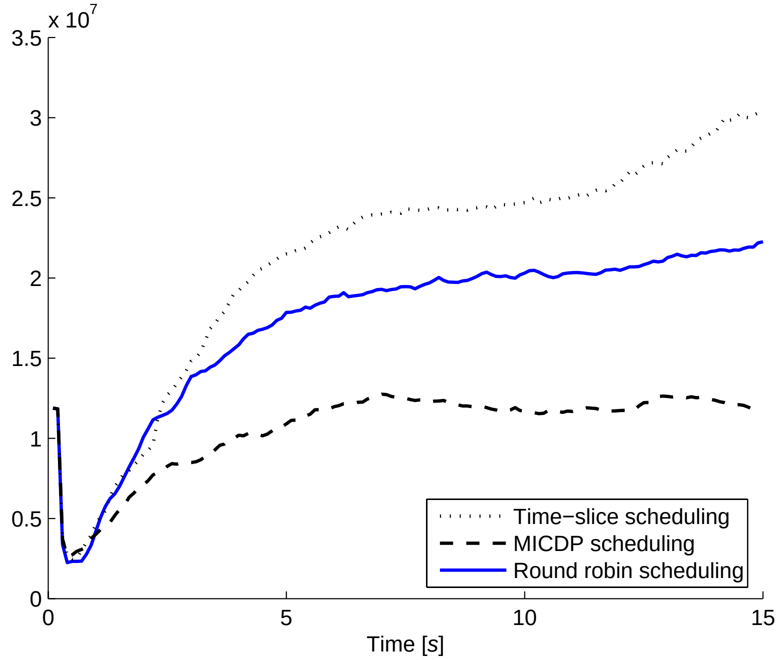


Figure 22: Average track-to-track Mahalanobis distance (AM)

Further work should concentrate on replacing the above presumptions with some more theoretical relations involving the state of the observed space, the sensor(s) characteristics and the required performance.

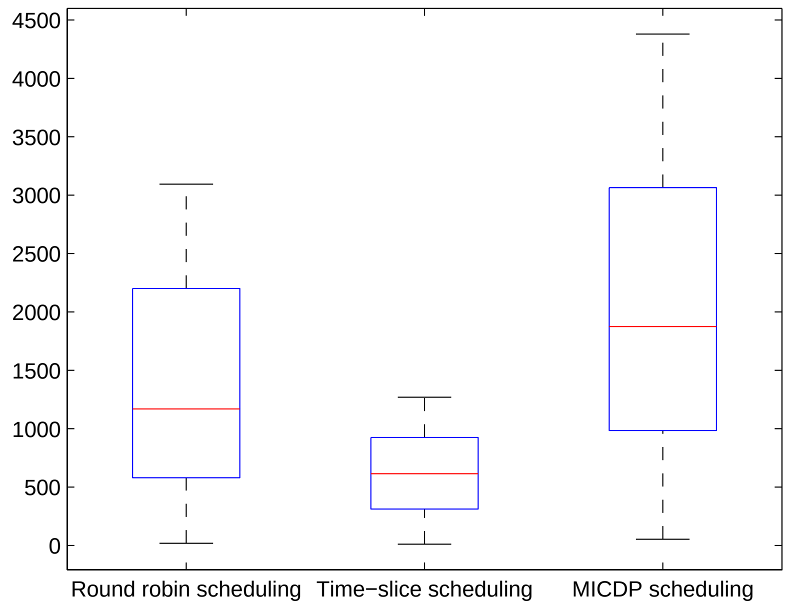


Figure 23: Total number of Discrimination Conflicts ($DC_{[1,...,15]}$)

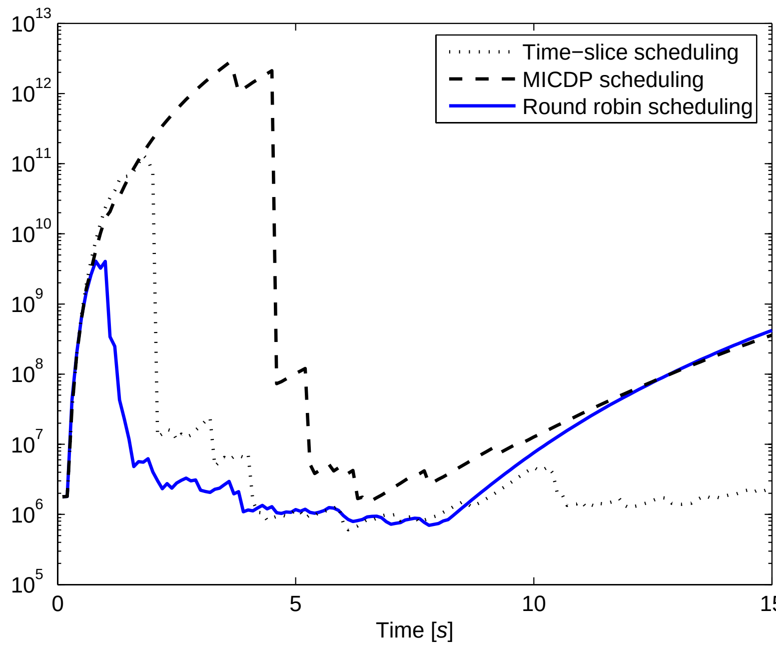


Figure 24: Average determinant of error covariance matrix ($ADET$)

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6 Conclusion

The target tracking application and the discrimination power problem were used to illustrate control and adaptation concepts in data fusion applications. A two-loop adaptation structure was defined to tackle the specific adaptive tracking problem. The outer loop dynamically defines and manages the clusters based on the concept of discrimination power, while the inner loop exploits the clusters for the adaptation purposes. The presented results showed the superiority of the time-slice adaptation-based strategy over static policies such as the round-robin scheduling strategy that was tested in this work. Furthermore, the time-slice method has shown to be superior to the minimum intra-cluster discrimination power method since the latter is myopic (*i.e.*, does not plan more than one update at a time).

Overall, the results presented in this report showed that the discrimination power can be improved by adapting the target tracking operations. In the light of these results, further works involving discrimination power should concentrate on. The following list gives a tentative ranking of problems to be investigated. This ranking is based on the challenges they pose and the preferences of the authors.

1. Identify and study specific military Command and Control applications on which discrimination power might have an impact. For example, an application to target engagement in dense environments, such as littoral, is being developed. The objective is to measure the impact of an improved discrimination power on the frequency and number of collateral damages.

2. Extend the concept of discrimination power beyond the tracking to include, for instance, the identification and the intent and capability assessment.

3. Integrate and experiment the discrimination power control strategies on some typical surveillance systems, using realistic military parameters and specifications.

4. Identify and study the inherent factors that might impact on the discrimination power.

5. Refine the clustering and scheduling strategies such that their variable parameters be adjusted depending on the state of the observed space and on the state and characteristics of the surveillance system.

6. Integrate the discrimination power control with other surveillance and sensing objectives, which should require finding new sensor scheduling methods.

7. Refine the sensor models and consider various types of sensors working together.

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List of symbols

α	Degree of belief (Bayesian coverage intervals) or significance level (χ^2 hypothesis testing)
η	Number of updates
$\mathbf{\Gamma}$	Process gain matrix
λ	Distance threshold
ψ	Update cycle
$\boldsymbol{\upsilon}$	Process noise
ξ	Constant
ζ	Track update control function
$ADET$	Average error covariance matrix determinant
AM	Average Mahalanobis distance
C	Cluster label
d	Statistical distance
$\mathcal{D}$	Dissimilarity matrix
DC	Discrimination Conflict
f	Frequency
$\boldsymbol{f}(.)$	State transition function
$\boldsymbol{F}$	Jacobian of $\boldsymbol{f}$
h	Track update period
$\boldsymbol{h}(.)$	Measurement function
h_c	Outer-loop period
h_s	Inner-loop period
$\boldsymbol{H}$	Jacobian of $\boldsymbol{h}$
k	Discretized time instant
K	Number of clusters
L	Distance threshold
n	Loop level or track label
nd	Number of dimensions of the state vector
N	Number of tracked targets in a scenario
$\boldsymbol{P}$	Covariance matrix of the state estimate

q	Process noise power spectral density
$\boldsymbol{Q}$	Track quality
R	Region label
$\boldsymbol{R}$	Measurement error covariance matrix
s	Track similarity measure
S	Schedule vector
t	Time label
$\boldsymbol{w}$	Measurement noise
$\boldsymbol{x}$	State vector
X	Abscissa
$\hat{\boldsymbol{x}}$	State estimate vector
Y	Ordinate
$\boldsymbol{z}$	Measurement vector

List of acronyms

C^2 Command and Control
CI Coverage Interval
EKF Extended Kalman Filter
MICDP Minimum Intra-Cluster Discrimination Power
TP Tactical Picture
VOI Volume Of Interest

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Glossary

The followings define a few expressions that are used in this work. Some of them where inspired from [3, 31].

- **Accuracy**
  - **Estimate accuracy:** The accuracy associated with an estimation represents its uncertainty with respect to the true value. Under the normality assumption, it is given by the standard deviation of the estimate posterior probability distribution function. Equivalently, accuracy can also be expressed as the standard deviation of the estimate's normally distributed random error with mean 0. Note that accuracy is often used to calculate the coverage interval of estimates.
  - **Sensor accuracy:** In case of a sensor, the accuracy is defined according to the measurement error probability distribution, which is assumed Gaussian. Practically, the value of accuracy specified in most sensing systems represents the standard deviation of the distribution.
- **Sensor resolution:** The resolution of a sensor is its ability to distinguish between objects that are very close in space. For example, a typical two-dimensional (2D) radar has its resolution defined for both range and bearing. Accordingly, range resolution is the ability of a radar system to distinguish between two or more objects on the same bearing but at different ranges. Angular resolution is the minimum angular separation at which two equal objects can be separated when at the same range.[7]
- **Similarity:** Similarity expresses a resemblance between two or more estimates with respect to the estimated features. It is represented by statistical measures that quantify the correlation between two or more estimates. For example, the resemblance can be quantified by evaluating the amount of the overlapping portion of the probability distributions of the features.
- **Dissimilarity:** Dissimilarity is the opposite of similarity. It expresses a difference between two or more estimates with respect to the estimated features. For example, the difference can be quantified by evaluating the amount of the non-overlapping portion of the probability distributions of the features.
- **Discrimination:** The process whereby two or more observed objects are distinguished.
- **Discrimination Power:** The capability (or power) to distinguish two or more observed objects. In target tracking, it is a measure of the dissimilarity between multiple target tracks distributed in the space.

[7] In [38], resolution is also defined as the finest change in input value.

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This report addresses the problem of discrimination power in target tracking applications. More specifically, a closed-loop approach to adapt the sensing and tracking operations is proposed and compared to the conventional open-loop and static approach. The objective is to control and maintain, over a certain volume of interest and by way of clustering and scheduling strategies, the level of discrimination power required by the mission objectives. The control strategy is based on two cascade loops. The outer loop uses clustering techniques to characterize the volume of interest in terms of discrimination power. This high level information is exploited by the inner loop to compute optimal track update and sensor scheduling strategy. The presented results show that the discrimination power can be improved by adapting the target tracking operations. This improvement could benefit tactical military surveillance operations such as contact/track correlation, target engagement, target identification and classification.

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